

Discriminating between alternative measures of overeducation

Verhaest, Dieter; Omeij, Eddy

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Discriminating between alternative measures of overeducation

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Discriminating between alternative measures of
overeducation

Abstract

Five overeducation measures are evaluated empirically on the basis of encompassing tests. The measures are based on job analysis (JA), worker-assessment of the required level to do the job (WAd), worker-assessment of the required level to get the job (WAg), the mean educational level of realized matches (RMmn), and the modal level of realized matches (RMml). Over- and undereducation are linked to wages, job satisfaction, mobility and training participation. For none of the outcome variables, the JA model is encompassed by another model. Given the risk on systematic errors, this is a sufficient condition to prefer a carefully conducted JA to any other measure. The most reliable solution is to use the JA measure as an instrument for the WAd measure.

Keywords: overeducation, underemployment, mismatch, measurement, encompassing

I. Introduction

A large amount of literature on the economics of over- and undereducation has emerged over the past years. There is substantial evidence that several outcome variables such as wages, job satisfaction, mobility and training participation are related to overeducation. Despite this growing interest, no uniform way of measurement exists. Hartog (2000) classified these measures into three categories. Firstly, subjective Worker self-Assessment (WA) measures are derived from survey questions to the level required to do (WAd) or to get (WAg) the job. Over- and undereducation is measured by comparing this level with the actual educational level. Secondly, Job Analysis (JA) bases the required level on the occupational classification of job experts. Thirdly, Realised Matches (RM) measures look at the difference between the actual educational level and the mean (RMmn) or modal (RMml) level within a person's occupation¹. Comparative research shows that results depend on the applied measure (Rubb, 2003; Verhaest and Omey, 2005b). JA is clearly the most attractive measurement (Hartog, 2000). Conceptually, it reflects the core idea of overeducation in the literature: overeducation as underutilization of skills. Furthermore, there are no reasons to expect systematic bias in measurement. However, a lot of researchers still prefer to use subjective measures since JA is a very costly exercise and requires frequent updates to adapt to changing technology. Additionally, explanatory variables such as job satisfaction or mobility may be influenced by the perception of being overeducated instead of objective overeducation.

The aim of this paper is to examine the reliability of the different measures on the

¹ Sometimes, worker self-assessment measures are based on direct survey questions to their over- or undereducation status. For surveys of the literature and extensive discussions on the applied measures, we refer to Halaby (1994), Green et al. (1999), Hartog (2000), Groot and Maassen van den Brink (2000), Verhaest and Omey (2004, 2005a), and Sloane (2004).

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basis of encompassing tests (see Mizon and Richard, 1984). In a measurement context, the application of encompassing or related approaches for non-nested hypotheses is rather seldom (see, e.g., Oczkowski and Farrell, 1998; Poor et al., 2001). The idea is simple: one measure should be preferred to another if its outcomes encompass the results of its counterpart. We link five overeducation measures to four outcomes: wages, job satisfaction, mobility and training participation. These outcomes represent the bulk of the literature on the impact of overeducation (see, e.g., Hersch, 1991; Allen and van der Velden, 2001; Verhaest and Omey, 2005b). So, there is a strong case for applying JA if this measurement would prove to be reliable within these different contexts.

The paper is structured as follows. In section II, we give an overview of potential errors and biases when analysing the impact of overeducation. The test procedure is explained in section III. In section IV, we deal with the data. In section V, we outline our empirical model. The results are overviewed in section VI. Finally, in section VII, we discuss the outcomes of the analysis and make some conclusions. Our results strengthen the use of JA. However, the most reliable solution is to instrument the WAd measure on the JA measure.

II. Potential biases and errors

A first potential bias lies in differences between the concept to be measured and the concept actually measured, i.e. the validity of the instrument. In the literature, overeducation is generally conceptualised in terms of an educational level that exceeds the minimal required level to do the job (Green et al., 1999). Starting from the technology of the job and the activities to be performed, JA clearly reflects this concept (Hartog, 2000). Also subjective measures on the basis of the required level to do the job are in line with this interpretation. Although closely related to this concept, the other indicators clearly measure something different. The required level to get the job, or the mean or modal educational level within

an occupation are not necessarily the same as the level to do the job. The minimal required level to get the job reflects a reservation educational level below which employers won't hire job applicants (Verhaest and Omeij, 2004). The gap between these two concepts is often termed qualification inflation and deflation (see, e.g., Green et al., 1999; Dolton and Silles, 2001). Defining the required level by the mean or median educational level may reflect educational mismatches resulting from searching and matching (Borghans and de Grip, 2000). However, it only measures frictional mismatches and neglects structural sources of over- and undereducation (Verhaest and Omeij, 2005a).

The second source of biases and errors results from the data collection and registration process, i.e. the reliability of the measures. The main critique on JA is about random measurement error. It is often argued that heterogeneity within occupations makes JA (and RM) measures more prone to this type of error (see, e.g., Halaby, 1994). This is true if the starting point of the occupational classification is the job title, and not the requirements. Apart from heterogeneity error, also classification error may cause these types of error. Contrary to job experts, respondents can rely on all relevant information. However, they lack uniform coding instructions. They may report the required level to get the job, current hiring standards, the median educational level for similar workers, or their own educational level. Verhaest and Omeij (2004) indeed found that random error explains a significant but small part of the variation of every measure. Social desirability may systematically bias subjective levels upwardly. This bias may be enforced if individuals are more likely to report their actual educational level. Oppositely, JA delivers an unbiased measure of the required level (Rumberger, 1987; Hartog, 2000). It is sometimes argued that technological progress biases JA levels systematically downwardly. However, this can be avoided by a regular update of the classification scheme or by using a scheme that starts from requirements instead of job titles. In this last case, the scheme should be flexible enough to incorporate changes in requirements.

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Highly problematic is when these errors are related to the variables of interest, such as job satisfaction, training participation, mobility or wages. Researchers are generally not merely interested in correlations, but in the causal impact of true over- and undereducation on these variables. Well known from the psychological literature is that answers to survey questions are interrelated. Context effects do not only influence answers on attitude questions, but also on non-attitude questions such as one's race (Martin et al., 1990). Respondents will try to keep a degree of consistency in their answers. Furthermore, temporal mood states strongly influences judgements (Schwarz and Strack, 1999). Finally, also social desirability bias leads to interrelated answers. All this creates a spurious relation between the outcome variables and overeducation if measured in a subjective way. It is clear that these problems are severe in the case of overeducation, a concept that, even among social scientists, has no unique interpretation. So, individuals that answer to be satisfied with their job will also tend to evaluate their match position in a more positive way. Being offered a permanent contract or not being fired may be used as an indication for the quality of their match. They may conclude that they were undereducated for their job since they were offered additional training. Or their personal wage may influence their judgement. After all, also researchers use these outcome variables as an alternative way to assess the degree of over- and undereducation or the quality of the match². This approach may be useful to examine overeducation in a different context if no direct measure is available, but not to assess the impact on the variable on which its measurement is based.

III. Test procedure

A way of testing which of two non-nested models should be preferred is the application of

² For wages, see, e.g., Gottschalk and Hansen (2003); for satisfaction, see, e.g., Chevalier (2003); for tenure, see, e.g., Bowlus (1995).

the encompassing test-principle³. For outcome variable y^* and respective overeducation measures x^a and x^b , consider the following models:

$$H_a : y^* = \beta_1^a x^a + \varepsilon^a$$

$$H_b : y^* = \beta_1^b x^b + \varepsilon^b$$

The encompassing principle is applied by adding the non-nested part of the second equation (i.e. x^b) to the first equation:

$$H_{ab} : y^* = \beta_2^a x^a + \beta_2^b x^b + \varepsilon^{ab}$$

The test is a simple F- or Likelihood Ratio-test of the new equation H_{ab} against H_a , and, similarly, against H_b . H_a is said to encompass H_b if H_a is not rejected against H_{ab} . The possible outcomes are summarized in figure 1.

“figure 1 here”

The interpretation of the outcomes depends on the type of measures being compared. Suppose that x^a is a valid measure (e.g., JA or WAd), and x^b not (e.g., WAg, RMmn or RMml). Since x^b is not valid, x^a should always be preferred. However, x^b is still useful if both concepts do not differ in reality. This is the case if the results of both models encompass each other (figure 1, cell 1). Then, researchers can still use the non-valid measure if a valid measure is not available. In the other cases, the measures differ substantially, and only one (cell 2 or 3) or both concepts (cell 4) are related to the outcome

³ For an overview, see Davidson and MacKinnon (1993).

variable. Suppose that both x^a and x^b are valid (e.g., JA is tested against WAd). If both measures encompass each other (cell 1), they generate statistically similar outcomes. Hence, both indicators are equally effective. Model H_a may encompass H_b , while H_b does not encompass H_a (cell 2). In this case, x^a should be preferred to x^b . In the opposite case (cell 3), we should prefer x^b . Finally, none of the models may encompass its counterpart (cell 4). Then, neither model is satisfactory, e.g. due to substantial errors in both measures.

These standard encompassing interpretations are only valid under the assumptions that $E(\varepsilon^a | x^a) = 0$ and $E(\varepsilon^b | x^b) = 0$. However, one may expect that the error term of one measure is spuriously correlated with the explanatory variable, e.g. for WAd in the likely case of the job satisfaction analysis. Then, the encompassing test procedure is equivalent to the specification test of Hausman (1978) for endogeneity. Suppose that $E(\varepsilon^a | x^a) = 0$ (e.g. for JA) and $E(\varepsilon^b | x^b) \neq 0$ (e.g. for WAd). A way to correct for the bias in measure x^b is to use the unbiased measure x^a as an instrument ($\hat{x}^b = \eta x^a$). If $E(\varepsilon^b | x^b) = 0$, the impact of the residuals of this estimation on y^* equals the impact of the estimated values \hat{x}^b . So, a test for endogeneity is based on the following equation H_e :

$$H_e : y^* = \beta_3^b (x^b - \hat{x}^b) + \beta_3^b \hat{x}^b + \varepsilon^e \Leftrightarrow y^* = (\beta_3^b - \beta_3^a) \hat{x}^b + \beta_3^b x^b + \varepsilon^e$$

The Hausman test is a test of the null hypothesis that $\beta_3^b = \beta_3^a$ or $(\beta_3^b - \beta_3^a) = 0$. Given

$\hat{x}^b = \eta x^a$, H_e can be rewritten as:

$$H_e : y^* = (\beta_3^b - \beta_3^a) \eta x^a + \beta_3^b x^b + \varepsilon^e$$

If $\eta \neq 0$, i.e. x^a is correlated with x^b , a test of the null hypothesis that $(\beta_3^{\hat{b}} - \beta_3^b) = 0$ is equivalent to a test of $(\beta_3^{\hat{b}} - \beta_3^b)\eta = 0$, i.e. the encompassing test. In this interpretation, the rejection of the model with the potentially biased measure x^b (cell 2 or 4) is a sufficient condition to prefer the usage of the alternative measure x^a . Which measure may be systematically biased can only be determined on the basis of theoretical considerations.

IV. Data

The analysis is based on the 1978 and 1980 birth cohorts of the SONAR data about the transition from school to work in Flanders. These cohorts consist of random samples of respectively 3002 and 2993 Flemish individuals, interviewed face-to-face during the last four months of 2001 and 2003⁴. The interview consisted of an extensive questioning of the educational and early labour market career. For the first job after leaving school⁵, we compute the over- and undereducation status of the respondents, based on the five measurement methods. A major advantage of an analysis of first jobs is that over-education measurement is not biased by additional human capital accumulation through experience and on-the-job training⁶. So, educational mismatches are more likely to reflect skill mismatches (see Allen and van der Velden, 2001). The first job is not observed for 22.0% of the individuals, mainly because they were still student at the age of 23 (15.4%). The analysis is restricted to those with observations on all of the five measures, with a first non-

⁴ For the 1978 cohort, some extra interviews were conducted in the first months of 2002.

⁵ The first job is defined to be the first job of at least one hour a week and tenure of at least one month. For an extensive description of the data, see SONAR (2003, 2005).

⁶ It is generally found in the literature that experience and tenure decrease (increase) the probability of being classified as overeducated (undereducated) (see, e.g., Groot, 1996; Sloane et al., 1996, 1999).

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self employed job inside Flanders (Brussels including) and who did not return to education after their first job. This reduces the potential sample to 3759 respondents. These school leavers entered their first job during the period 1996-2003. For the derivation of the over- and undereducation status, the following educational levels are defined: less than lower secondary (<LS: 3.9% of potential sample), lower secondary (LS: 9.3%), higher secondary (HS: 50.4%), lower tertiary (LT: 25.8%) and higher tertiary education (HT: 10.6%).

Occupations are coded following the 2001 update of the 1992 Standard Occupation Classification of Statistics Netherlands (CBS, 2001). An advantage of this classification is that it starts from the complexity and content of the tasks to be executed on the job, and not from the job title (cf. supra). The classification is based on five functional levels that correspond to our five distinguished educational levels. It is a flexible classification that enables to classify jobs with a similar title at different functional levels⁷. The coding was based on open answer information on the following items: tasks to be executed, job title and activity of the firm. Interviewers were urged to ask to all details of the tasks to be executed and activities of the firm. Additional information used was the number of individuals being managed, self-employment and firm size. The WAd measure is based on: ‘What is, according to your own opinion, the most appropriate educational level to do your job?’. Furthermore, respondents were asked: ‘Was a qualification required to get your job?’. In the case of a positive answer, they were asked: ‘To get your job, what educational level were you required to have?’. On the basis of this information, the WAg measure is computed. Finally, the mean and modal educational level for each 2-digit CBS occupation was computed to derive the RMmn and RMml measures⁸. The mean and modal

⁷ Clerk occupations, e.g., are found at four of five functional levels. In the 1988 ISCO classification (ILO, 1990), all these jobs are grouped under one basic job title and are assigned one single ISCED level.

⁸ In line with the literature, the RMmn overeducation (undereducation) status is defined by

level are probably biased if derived from the 1978 and 1980 SONAR cohort since the first job is not observed for those who were still at school at the age of 23. So, we derive the mean and modal educational level within each occupation from the 1976 SONAR birth cohort. A follow-up survey was conducted for this cohort at the age of 26, delivering observations on the first job for 92.7% of the school leavers (see SONAR, 2004)⁹.

Table 1 reports the incidence of over- and undereducation for the analysed sample on the basis of the different measures. The figures diverge substantially between the different measures. The incidence of overeducation ranges from 8.7% for RMmn to 51.0% for JA. The incidence of undereducation ranges from only 4.7% for WAg to 21.8% for RMml. These differences are in line with the outcomes of other studies that also measured over- and undereducation in various ways for the same dataset of individuals¹⁰. They further underline the importance of additional research on the reliability of these measures.

“table 1 here”

V. Empirical model

We estimate the effect of different educational mismatch measures on job satisfaction, mobility, training participation and wages. For each of these variables, we apply the

years of education that are more (less) than one standard deviation above (below) the mean (see, e.g., Verdugo and Verdugo, 1989; Groot, 1996).

⁹ The results of the RM measures derived from the 1978 and 1980 cohort were encompassed by those on the basis of the 1976 cohort for all of the explanatory variables. We do not include the respondents of the 1976 cohort into the estimations since the survey did not include questions that enable to compute a WAd measure.

¹⁰ For an overview of these studies, see Verhaest and Omey (2005a).

following basic model for measure i :

$$Y = \alpha_i + \mathbf{X}\beta_i + \gamma_i YEDUC + \delta_i YOVER_i + \varphi_i YUNDER_i + \varepsilon_i$$

With Y = dependent variable (job satisfaction, mobility, training participation and wages), \mathbf{X} = a vector of control variables, $YEDUC$ = years of education, $YOVER$ = years of overeducation, $YUNDER$ = years of undereducation. Years of education are based on the minimal study length of the educational levels: <LS = 6 years, LS = 10 years, HS = 12 years, LT = 15 years and HT = 16 years. Since $YEDUC \equiv YREQ_i + YOVER_i - YUNDER_i$, this model is equivalent to the generally applied ORU-specification (see Hartog, 2000), but enables to separate the effect of measurement from the effect of years of education. The non-nested part consists of $YOVER$ and $YUNDER$.

For the wage analysis, net monthly starting wages are deflated and converted into hourly earnings and OLS is applied for $\text{LN}(\text{WAGE})$ ¹¹. Job satisfaction is based on a scale from 1 (very unsatisfied) to 5 (very satisfied) and is estimated on the basis of an ordered probit specification. Mobility out of the first job is measured by a change in function and/or firm and estimated through a Cox proportional hazard model. For the training participation analysis, we apply a binary probit regression whereby the training variable is coded with value 1 if the school leaver participated in formal job training inside or outside the firm during the first job.

Two specifications of models are estimated, depending on the control variables (\mathbf{X}) that are included. Specification A includes a fixed number of individual and job characteristic variables¹². Job satisfaction and mobility may depend on the wage level and

¹¹ Outliers (hourly wages of < 2.5 EURO and > 25 EURO) are excluded from the analysis.

¹² The following control variables are included: inactivity duration between school leaving and job start, father's and mother's years of education, dummies for having a father (1

the offered training opportunities in the job. Training may also exert an impact on wages, while training participation may depend on the observed job length. So, specification B differs by outcome and includes these extra control variables. Job duration may be endogenously related to training participation. So, we apply a two step approach for the training participation analysis: potential observed job duration, i.e. duration between job start and the survey date, is used as an instrument for observed job duration. LN(WAGE) and a dummy for formal training participation are included in the mobility and job satisfaction analysis. The formal training participation dummy is also included in the wage analysis¹³.

The first job is not observed for a substantial part of the sample and this sample selection may bias the results (cf. Heckman, 1979). Some additional tests were executed to assess whether this may affect our conclusions. We estimated maximum likelihood heckman selection models for the wage analysis and maximum likelihood probit models with selection for the training analysis (see STATA, 2003)¹⁴. In a first selection model, we

dummy) and mother (1) being regularly unemployed during the phase of secondary education, gender (1), non-European descent (1), cohabiting at job start (1), having a child at job start (1), firm size (3), industry (11), professions (3), shift-work (1), night-work (1), temporary (1) and part-time contract (1), region of employment (4) and quarter of job start (31).

¹³ Training participation may be delayed, what is problematic for the wage analysis since starting wages are analysed. Training is also endogenously related to mobility in this case. Yet, in line with the human capital prediction that training is provided at the job start, we did not note a significant impact of observed job duration on the probability of formal training participation.

¹⁴ The selection equation included the same individual characteristic variables as the outcome equation (cf. supra), region of residence (4 dummies), and duration between the

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only included school leavers in the selection equation. In a second model, we also included those who were still at school at the age of 23. Yet, we did not find any evidence on sample selection effects since the outcome equation was always found to be independent from the selection equation. Moreover, the encompassing test outcomes were identical to those on the basis of the standard estimations. The sample selection problem is particularly relevant for the HT educated¹⁵. We re-estimated the models for every outcome variable, but excluded those with a HT degree. Also this did not change our conclusions. So, we only report the results on the basis of the full sample.

VI. Results

Adding the educational mismatch variables (*YOVER* and *YUNDER*) to the equation always leads to a significant improvement of the model (see table 2). Which measure delivers the largest contribution to the model depends on the outcome variable. While JA delivers the largest contribution to the explanation of LN(wages), it is the WAd measure that explains the largest part of the variation of job satisfaction and job mobility. With respect to training participation, WAg delivers the largest contribution. The results are in line with previous findings in the literature: overeducated workers earn less, are less satisfied, are more mobile and participate less in training in comparison with adequately educated workers with a similar educational level¹⁶.

date of the first interview in the survey and the date of the individual interview. This last variable is independent from the outcomes but has a significant impact on selection.

¹⁵ Most of the scholars at the age of 23 were student at the HT level (74.3%). Moreover, those with a HT degree were also overrepresented among the school leavers without a job at the age of 23: 35.6% of this group had a HT degree.

¹⁶ An overview of the literature on earnings is given by Hartog (2000), and for the other

“table 2 here”

We concentrate on the encompassing test results (see table 3). There are few differences in test outcomes between the two model specifications. Moreover, these differences do not affect the general conclusions. Only for the RM measures in the case of the training participation analysis, mutual encompassing between two measures is noted. This confirms previous findings that different measures lead to statistically different outcomes. Both the JA and WAd measure results are never encompassed. Furthermore, the WAg measure results are in some cases encompassed by those of the WAd measure. Finally, the RM measures are never able to encompass the results of any of the three other measures, while their results are encompassed at least once by every other measure.

“table 3 here”

VII. Discussion

The results of the JA and WAd measures are never encompassed by any of the non-valid measures. Thus, JA or WAd should always be preferred to RM or WAg measures of overeducation. Encompassing tests between JA and WAd deliver no preference: neither JA encompasses WAd, nor WAd encompasses JA for any of the outcome variables. At least for the job satisfaction analysis, this result may sound surprising since the relationship between objective conditions of life and subjective well-being is generally found to be weak (Schwarz and Strack, 1999). It illustrates that both aggregation error and classification error should not be greater on the basis of JA if the analysis is carefully

outcome variables by Verhaest and Omeij (2005b). Our results are available upon request.

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conducted and a requirement based classification is used. Of course, WAd is a cheap alternative to the relatively costly JA. However, if carefully implemented, JA can also be conducted on a survey-based manner and does not necessarily require a visit at the workplace.

The test can also be interpreted as a Hausman specification test for endogeneity. Several sources of measurement error may result in spurious correlation between the outcome variables and overeducation if measured by WAd. These problems may be particularly severe in the case of the job satisfaction analysis. Oppositely, we have no reasons to expect systematic bias of the JA measure with any of the outcome variables. On the basis of these theoretical considerations, the rejection of the WAd model is a sufficient condition to prefer the usage of JA. Since both measures lead to statistically different outcomes, JA is a more secure option. Nevertheless, the ideal solution is relying on both measures by instrumental variable techniques. Using the WAd measure as an instrument variable for the JA measure corrects for the bias caused by random error, but introduces the systematic bias of the WAd measure. Oppositely however, using the JA measure as an instrument for the WAd measure is a more reliable solution. In this way, error in the WAd measure is corrected for without introducing some new systematic bias.

VIII. References

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Figure 1: Possible encompassing outcomes

		H_a encompasses H_b ?	
		Yes	No
H_b encompasses H_a ?	Yes	1	3
	No	2	4

Table 1: Incidence of over- and undereducation for the analysed sample (N = 3759)

	JA	WAd	WAg	RMmn	RMml
Overeducated	51.0%	27.2%	44.2%	8.7%	11.6%
Undereducated	7.8%	9.4%	4.7%	15.8%	21.8%

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Table 2: Contribution of *YOVER* and *YUNDER* to the model (\$)

	LN(Wages)	Job Satisfaction	Mobility	Training
<i>Specification A</i>				
JA	58.7**	94.4**	49.5**	37.1**
WAd	25.1**	251.3**	107.8**	49.8**
WAg	21.5**	92.8**	46.1**	55.4**
RMmn	44.6**	48.4**	35.5**	7.8*
RMml	51.5**	36.7**	24.6**	8.9*
<i>Specification B</i>				
JA	55.0**	64.9**	29.0**	36.8**
WAd	22.4**	214.4**	84.0**	47.1**
WAg	18.7**	73.0**	31.0**	54.6**
RMmn	42.7**	34.2**	24.3**	8.3*
RMml	49.4**	25.5**	15.1**	9.4**

Applied estimation procedure: LN(Wages): OLS (A: N=3303; B: N=3300); Job Satisfaction: Ordered Probit (A: 3463; B: N=3300); Mobility: Cox proportional hazard (A: N=3463; B: N=3300), and Training: Binary Probit (A: N=3460; B: N = 3460).
(\$) F statistic for LN(Wages), and Likelihood Ratio Chi² statistic for other analyses.
*: significant at 5% level; **: significant at 1% level.

Table 3: Encompassed models for different outcome variables (\$)

	LN(Wages)	Job Satisfaction	Mobility	Training
<u>Specification A</u>				
JA – WAd	-	-	-	-
JA – WAg	-	-	-	-
JA – RMmn	-	RMmn	-	RMmn
JA – RMml	-	RMml	-	RMml
WAd – WAg	-	WAg	-	-
WAd - RMmn	-	-	-	RMmn
WAd – RMml	-	-	-	RMml
WAg – RMmn	-	-	-	RMmn
WAg – RMml	-	-	-	RMml
RMmn - RMml	RMmn	RMml	RMml	RMmn / RMml
<u>Specification B</u>				
JA – WAd	-	-	-	-
JA – WAg	-	-	-	-
JA – RMmn	-	RMmn	-	RMmn
JA – RMml	-	RMml	RMml	RMml
WAd – WAg	-	WAg	WAg	-
WAd - RMmn	-	-	-	RMmn
WAd – RMml	-	-	-	RMml
WAg – RMmn	-	-	-	RMmn
WAg – RMml	-	-	-	RMml
RMmn - RMml	RMmn	RMml	RMml	RMmn / RMml

(\$)

(\$) For the wage analysis, e.g., the RMmn model is encompassed by the RMml model; tested on the basis of an F-test for LN(Wages) and on the basis of a Likelihood Ratio-test for the other analyses; evaluated at 5% significance level.